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Official logo recognition based on multilayer convolutional neural network model

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ABSTRACT

Deep learning has gained high popularity in the field of image processing and computer vision applications due to its unique feature extraction property. For this characteristic, deep learning networks used to solve different issues in computer vision applications. In this paper the issue has been raised is classification of logo of formal directors in Iraqi government. The paper proposes a multi-layer convolutional neural network (CNN) to classify and recognize these official logos by train the CNN model on several logos. The experimental show the effectiveness of the proposed method to recognize the logo with high accuracy rate about 99.16%. The proposed multi-layers CNN model proves the effectiveness to classify different logos with various conditions.

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1. INTRODUCTION

Recently, logo classification [1]–[4] has an significant direction in computer vision applications due to the vital role of this application to save time and effort. Therefore, an automated document classification becomes urgent requirement make it easier to search for particular documents. In the last years, there has been a lot of interest in document image processing and comprehension for a range of applications such as digital repositories, internet publishing and surfing, online shopping, and official automation systems. The identification of logos is a reliable method for document image analysis and retrieval. Logos used to mark the source of a text. Logos are 2D shapes with a variety of types that are usually a mix of graphical and text elements [5]. Logo detection and recognition belong to two fields in computer science (computer vision and pattern recognition), where the logo recognition considered as a special case of image recognition [6]–[8]. Usually the logo consists of mixed texts and graphic symbols according to its design. Therefore, it considered as a very difficult task to discover, especially when it iffers from the trained logo in terms of its size, rotation, resolution, lighting, colors, and many more.

In this work, the main contribution is proposing a new convolutional neural network (CNN) architecture to recognize and classify several types of logos with different characteristics. This model is robust to changes in the rotation, scales and lighting conditions. Moreover, the model applied on different logos with different characteristics. The results show the proposed model has an acceptable and reliable outcome on logo classification.

The organization of this paper as following: in section 2, literature review is explained. Section 3 show the proposed framework that contain the dataset that used in the experiments and proposed CNN

model, and a comparison among recent work on logo classification. Finally, the results will be conduct in section 4 follow by section 5 to draw the conclusion.

– Literature review

Logo recognition has a main role in different areas such as security, advertisements, and classify different bodies document using their own logs. Therefore, many studies have been introduced with different methods to tackle this issue. Some of the methods based on hand graft features and others using deep learning algorithms. Some of these studies have been explained below.

Hassanzadeh and Pourghassem [9], a method based on handgraft features, where a new spatial feature extraction for logo recognition proposed using k-nearest neighbor (KNN) to detection and recognition a novel logo. This feature was identified based on histogram of object occurrence in a new tessellation of logo image. The experiment results emphasized effectiveness of the proposed algorithm in noisy and separated part logos.

Handcraft features are used to classify the logos [7]–[13]. One of these methods were presented in [7]–[11], where histogram of oriented gradients (HOG) and scale-invariant feature transform (SIFT) have been applied to printed image for recognizing logo. As a consequence of the experiment, HOG outperforms SIFT significantly, where the HOG approach finds logos with a precision of 54% and a recall of 29%. While, the SIFT method only obtains 21% precision and 14% recall [10] and 93.50% precision and 77.94% recall, and 85.02% F1 in [11] respectively.

Llorca *et al.* [12], Sulehria and Zhang [13] introduced method to classify vehicle logo. The former one presented schema named “LogoSENSE” that consist HOG applied on logos with fixed size, with a max-margin loss equipped support vector machine (SVM) to decrease number of false positives. And in [13] the work based on mathematical morphology as a shape descriptor to classify the logo. Handcrafts features are weak for the noise and image distortion.

Özay and Sankur [14] an automatic TV logo classification system by static regions given by time-averaged edges subjected to post-processing operations. Once the region of interest of a logo candidate is identified, TV logos are classified via their subspace features. Comparative analysis of features has justified that ICA-II architecture yields the most discriminative with an accuracy rate of 99.2% in a dataset of 3040 logo images (152 varieties). Online tests for both detection and classification on running videos have achieved 96.0% average accuracy. A more reliable logo identifier will be feasible by improving the accuracy rate of the extracted logo mask.

Kumar *et al.* [15] proposed a method to classify the color logos by extracted the general features (color, shape, texture) of logos and merge these features in different ways for classification as either a logo with only text or a logo with only symbols or a logo with both text and symbol. The K-NN classifier is used for classification. Further, the system is categorized in the logo if the logo image consists of a text only or symbols only, or some image has both the text and symbols at the same time.

The KNN method is used in the classification. It employs the dataset called UoMLogo. This dataset is generally divided into three classes. They are both logo image (a mix of text and symbol), text logo image and symbol image. The outcomes show that the accuracy in text image, image, and blend text and image is 42.06, 43.58 and 48.98 respectively [15].

Multi-level context-guided classification method with object-based convolutional neural networks (MLCG-OCNN) proposed in [16], this model consists of an object-level contextual guided object-based CNN and is applied to carry out per-object classification by using image segmentation and merging the high-level features of spectral patterns, geometric characteristics, and contextual information. Then, with the help of the conditional random field (CRF), the per-object classification result is further refined by means of the pixel-level contextual guidance. The results showed the method achieves remarkable classification performance (> 80%). Compared with the state-of-the-art architecture DeepLabV3+, the MLCG-OCNN method demonstrates high computational efficiency for very high resolution imagery (VHRI) classification (4–5 times faster).

Patalappa and Chandramouli [17] worked on dataset of 450 TV broadcast channel logos (Indian channels) like (sports, movies, kids and cartoon, and entertainment) through different data augmentation techniques to expand the logo corpus for classifying logo using deep learning (YOLO v2). Su *et al.* [18], proposed a multi-perspective cross-class (MPCC) domain adaptation method to classify a fraction of logo classes whilst the remaining classes are only annotated with a clean icon image. The experiment results in extensive comparative experiments show the advantage of MPCC over existing state-of-the-art competitors on the challenging Queen Mary University of London (QMUL)-OpenLogo dataset benchmark.

Oliveira *et al.* [19] presented an automatic graphic logo detection system for FlickrLogos-32 dataset that robustly handles unconstrained imaging conditions based on fast region-based convolutional networks (FRCN), two CNN models pre- trained with the ImageNet large scale visual recognition challenge (ILSVRC) ImageNet dataset have been used. The experimental results achieved a top recognition F1-score of 0.909 with a base learning rate of 0.001 at 30000 iterations and with a threshold of 0.4. A method had been proposed in [20]

for logo recognition using deep learning. Logo recognition is essential in numerous application domains [21]. The study carried the experiments on two datasets: FlickrLogos-32 indicates 32 distinctive logo brands and the Logos-32plus dataset that contains more elements than FlickrLogos-32. Consequently, the Logos-32plus is better than FlickrLogos-32. Also, deep learning has been applied on 2000 logos from 295K pictures gathered from Amazon in [21] based on using deep learning networks.

Su *et al.* [8] the new technique to incremental learning called Scalable logo self-co-learning (SL2) described is capable of autonomously self-discovering noisy web imagery. Furthermore, using a big (2,190,757 pictures of 194 logo classes) logo dataset called "WebLogo-2M" by a programmed web information assortment and handling technique, the evaluations demonstrate the superiority of the proposed SL2 method over the state-of-the-art. Karimi and Behrad [22] enhanced the discrimination of the logo by employing some strategies of deep convolutional neural networks (DCNNs). Firstly, the combination of the features extraction and classification is employed by pre-trained deep models and SVM classifiers. Secondly, the logo recognition is adjusted by present pre-trained deep models. Finally, fine-tuned DCNNs outputs are merged by a voting algorithm in parallel structures.

Tüzko *et al.* [23] suggested to use an open set logo retrieval method that is better than closed set logo retrieval approaches because it has a number of stages that are detected, compared, and retrieved the logo from the images that are based on the convolutional neural networks (CNNs). The detection stage is faster region-based convolutional neural network (R-CNN) detected and extracted the object features from the image and then classified them. After that, the comparison stage is taking the extracted logo features from the detection stage and compares them with query samples in the database by using cosine similarity.

Hou *et al.* [24], the authors used the merge of the popular methods for logo classification. Firstly, the fine-tuning CNN architectures are produced four deep representations. These deep representations are merged with a number of imitative classifiers for running the logo classification. The proposed method is applied on the building Logo-405 dataset.

Bianco *et al.* [25] used different methods to characterize the images. Firstly, the recognition pipeline is taking the input image and extracted object proposals regions. Transformation pursuit is applied on the images for warping to a common size, increase the training data set and produce an expanded query. Finally, a CNN are applied for extracting the features and a SVM are used for recognizing and classifying the logo.

Iandola *et al.* [26] utilized three examples of DCNN architectures that are GoogLeNet-GP, GoogLeNet-FullClassify and Full-Inception to solve the variety of logo resolutions. So, the logos have been classified by applying these architectures. Finally, the logos are detected with their location by using the features of raw images and proposed region. Based on the results of the previous studies deep learning give an acceptable and reliable results comparing to classical methods. As a result, we propose a new CNN model to recognize logo; next sections show the details of this model.

2. PROPOSED FRAMEWORK

The framework of the logo recognition based on using CNN model. The deep learning prove the effectiveness in the recognition applications. Therefore, CNN model was suggested to address logo recognition issue. The model contains multi layers as explained in Table 1 with 2D convolutions and many max pooling layers. In the next sections the proposed method will be explained in details.

2.1. Dataset

In this paper, logos were collected manually for 25 ministries and establishments in Iraq for each of them 10 logos with various sizes, color, resolutions, lighting. To explain more on this collected datsetset, Figure 1 shows a sample of our dataset. First row example on higher ministry, second row represent college of science at University of Kerbala and so on.

2.2. Proposed CNN architecture

The proposed method based on using CNN model to classify different logos. These logs have different condition variables such as rotation, scales and different backgrounds. The proposed CNN model as shown in Figure 2 contains of 3 layers of (2D) convolutional with 3 layers of Max_pooling. The Table 1 gives a summary about the suggested CNN architecture.

2.3. Preprocessing step

In this step the whole dataset are resized to 224×224 to prepare to the input layer. In the following layers the features will be extracted. To avoid overfitting the rectified linear unit (ReLU) activation function was used with data augmentation. Followed by max pooling layers to extract the informative features from the raw data. Max pooling based on selecting the max value in the selected window. Figure 3 explains as an example of the max pooling.

Figure 1. Samples of the dataset

Because of the few numbers of samples, data augmentation has been used to increase the number of the dataset by using different transformation (scale and rotation). The augmentation gives a reliable number of samples for each logo. This method can be used when the dataset is few. By using this transformation, the size of dataset become reliable as an input to the CNN. The CNN is known that it needs a huge data to train as a result the data augmentation is the suitable solution of this issue when the size of the dataset is small.

The overview performance for the proposed model and it is an exact implementation of the conceptual model that used while learning how to measure the number of learnable parameters in a CNN. From Table 1, there were 2432 learnable parameters in the first convolutional layer, we also determined that the second convolutional layer had 25632 learnable parameters also the third layer had 25632 and the output layer had 82976 parameters, for 136,672 learnable parameters in the entire network. Table 2 depicts a comparison among the different method applied on this area "logo recognition". From the table, the outcomes of the proposed method give a motivation to consider the CNN to recognize the logos.

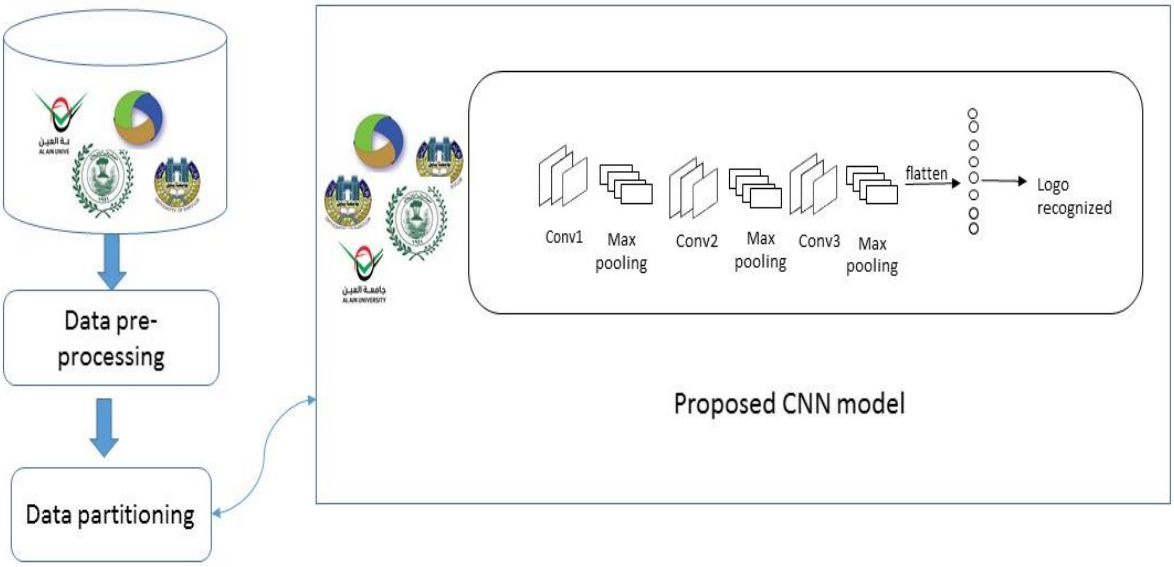

Figure 2. Proposed CNN structure for logo classification

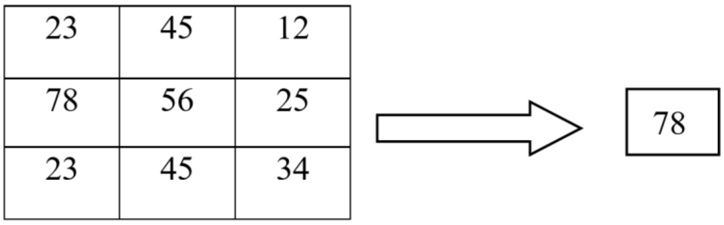

Figure 3. Max pooling

Table 1. Model "sequential_1"

Layer (type)	Output Shape	Param #
Conv2d_3 (Conv2D)	(None, 96, 96, 32)	2432
Activation_4 (Activation)	(None, 96, 96, 32)	0
Max_pooling2d_3 (MaxPooling2)	(None, 48, 48, 32)	0
Conv2d_4 (Conv2D)	(None, 44, 44, 32)	25632
Activation_5 (Activation)	(None, 44, 44, 32)	0
Max_pooling2d_4 (MaxPooling2)	(None, 22, 22, 32)	0
Conv2d_5 (Conv2D)	(None, 18, 18, 32)	25632
Activation_6 (Activation)	(None, 18, 18, 32)	0
Max_pooling2d_5 (MaxPooling2)	(None, 9, 9, 32)	0
Flatten_1 (Flatten)	(None, 2592)	0
Dense_1 (Dense)	(None, 32)	82976
Activation_7 (Activation)	(None, 32)	0
Total params: 136,672		
Trainable params: 136,672		
Non-trainable params: 0		

Tabel 2. Comparsion of different method applied on logo recognition

Paper citation	Application	Dataset size	Pre-processing	Result and approach
[1]	Applied segmentation and the spatial density for detecting the logo	–	The logos are translated, scaled, orientated, and degraded	After eight test models, the detection rate is 94.74%
[5]	– Compared between HOG and SIFT methods in logo detection – The HOG is better than SIFT after HOG perform transformation image (resizing and rotation)	– A local news agency contains images with from 10 companies' logos (32–93 images for each logo)	Rotated and inclined an image before HOG detection	– SIFT method achieved 20.6% precision and 14% recall – HOG method achieved 33.7% precision and 39.5% recall
[6]	Applied HOG histogram for visual representations of target brand logos and used SVM classifier	– 3060 web page training – 1979 unique snapshots	–	– 93.50% precision – 77.94% recall score – F1-scores 85.02%
[7]	Identify TV logo by using – Time-average edges for logo detection – ICA2 features for logo classification	3040 logo images database	–	– 99.2% accuracy of logo images – 96.0% average accuracy of running video
[9]	Classify VHRI by MLCG-OCNN proposed method in two level – Object-level is evidenced per object classification – Pixel-level is refined the classification result	– 6000×6000 pixels of each the potsdam images – 2817×2557 pixels of the largest Vaihingen images	Resize operation of the object	– classification performance > 80% from traditional method – 4–5 times faster in computational efficiency for VHRI classification
[12]	Recognized the brand by using graphic logo detection system and FRCN with transfer learning	– ILSVRC (1000 categories and 1.2 million images) – FlickrLogos-32 (32 different brand logos, 70 images per class/brand logo and 6000 non-logo images)	Used horizontally flipping the training images for the data augmentation	Used mAP to obtain the results at 60000 iterations
[14]	Recognize the logo by two modes: – Universal logo detector to learn the characteristics of a logo and find the regions of a logo – Logo recognizer to classify the logo by nearest neighbor and triplet-loss with proxies	– Product logo (PL2K) of 2000 logos from 295K images – FlickrLogos-32 of 32 logos from 8K images	–	– 97% recall -with 0.6 mAP on PL2K – 0.565 mAP on FlickrLogos-32
[17]	Open set approach, searched and retrieved a large-scale unseen logo and a new domains by an one query sample based on CNN	– 871 brands – 11,054 logo images	–	Average precision (0.368–0.464)
Our proposed method	CNN Model	Collected dataset from google	–	99.16%

3. EVALUATION THE PROPOSED MODEL

In the experiments, dataset split into 80%–20% train/test respectively. The accuracy rate for the dataset is 99.16%. The cross validation was achieved on this dataset to improve the outcomes. The model success to recognize multi official logo with different characteristics (different scale and texture). The optimal epoch that used in the experiments is 20 which prove the significant results to classify the logos. Trying different epochs in the training phase was applied but as an optimal number that give an acceptable.

4. CONCLUSION

In this paper, a new CNN model has proposed to recognize the various types of logos. CNN has a vital role in classification and recognition problems. Based on that, the proposed work employs CNN to recognize the logos. These logos represent an official logo of Iraq government ministries. The findings present that the suggested model has an effective role to recognize and classify these logs effectively.

The accuracy rate of the framework is 99.16%. This percentage make the model an acceptable and reliable. As a future work the system can be developed to manipulate the logo to distinguish between real and fake logos.

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